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ORIGINAL ARTICLE

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Locating and identifying sound knots and dead knots on sugi by the rule-based color vision system

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Abstract Knowledge of the occurrence of sound and dead knots on the surface of sugi is important for the classification and application of the material. This study examined a color vision system for detecting sound and dead knots on sugi. The system can be conceptually divided into three components: a CCD-camera scanning system, an image-segmenting module, and a rule-based defect identifying module. The results showed that the potential defect regions could be located by Otsu's threshold algorithm in conjunction with *t*-test analysis. The accuracies of locating sound knots and dead knots were 92.6% and 97.1%, respectively. The rule-based approach was used to identify sound and dead knots and the identifying accuracies for sound knots and dead knots were 92.0% and 94.1%, respectively. The overall detection accuracy of the system was 87.6%. The results indicated that the rule-based color vision system is an efficient means of detecting sound knots and dead knots on sugi.

Key words Wood defects · CCD-camera · Image processing · Color vision system · Sugi

Introduction

Sugi is the main wood species in Japan. However, the presence of many defects such as splits, holes, sound knots, and dead knots is well recognized. Detection of defects is performed by a skilled worker. However, human inspection is unsatisfactory because of subjective judgment. To automatically detect wood defects, optical, ultrasonic, microwave, nuclear magnetic resonance, X-ray, and temperature gradient methods have been used.[1–3] The optical method has been recognized as a promising technique and some optical systems have been developed to detect wood surface features. Quite recently, the color line scan camera was used to automatically optimize crosscut and to sort red oak edge panel parts.[4,5] Color feature histograms were used to separate wood defects into eight categories.[6] However, the appearance of wood varies greatly and there are no two boards or defects that have the same properties of color or texture.[7] Because there are still many problems associated with the detection of defects, it is necessary to develop a new detection system for automatic wood inspection.

In our previous report, we discussed the possibility of using a laser scanning system to detect splits and holes in sugi from thickness information.[3] In this article, we report on a rule-based color vision system that has been developed to detect sound knots and dead knots using color information.

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Experimental

The materials selected for the experiment were sugi samples measuring 1000 × 300 × 20 mm. All the samples were machined with a planer under the same conditions. The feeding speed was 15 m/min and the cutting speed was 30 m/s. The schematic diagram of the detection system is shown in Fig. 1. It consisted of a CCD-camera (Victor KY-F350, Victor JVC), two flood lamps (Toshiba reflector 150 WF), a computer numerical control (CNC) working table (Funuc M180 series), and a host computer equipped with a software system developed and installed by the authors. Samples were placed on the two-dimensional CNC working table and illuminated by two flood lamps from two sides. By adjusting the height and the focus of the digital camera, images were captured at 60 dpi and they were recorded as 24 bit per pixel (BPP) color images of dimensions of about 270 × 200 mm. The computer program was written in Visual Basic 6.0 (enterprise edition) as code resource. The flow chart of the program is shown in Fig. 2.

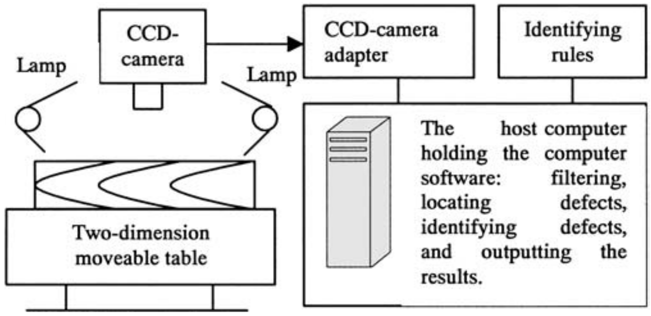


Fig. 1. Schematic diagram of the system

Image processing algorithms

After capturing and inputting the image, the color image was separated into R, G, and B signal images. In the present study, all the image processing operations were performed on the R signal image (Fig. 3) to improve the system efficiency. The image captured by the CCD-camera contained some unwanted image details, especially the annual ring structure for sugi. To avoid the segmenting artifacts caused by these image details, a simple spatial filter for equal-weighted averaging over a neighborhood was used.[8]

To separate pixels of clear wood from pixels that might be a potential defect, Otsu's method was adopted in conjunction with the *t*-test. First, the *t*-test analysis was performed.[9] The whole image was subdivided into subsets of 64×48 pixels. Then the potential defect subsets were classified by the operation based on a statistical *t*-test for equality of average R signal intensities between the subset and clear wood within the image. The clear wood was assumed to be 70% of the whole image. The steps associated with using the *t*-test are given below.

Step 1

The R signal intensity histogram and percentile histogram of the whole image were computed. Then the mean and variance of the range from the 15th percentile to the 85th percentile were computed. It can be described by the following formulas:

$$M_{\mathrm{R}70\%} = \frac{\sum_{i=v(15\mathrm{th})}^{v(85\mathrm{th})} c[g(i)]\cdot g(i)}{t\{c[g(i)]\}} \tag{1}$$

$$V_{\mathrm{R}70\%} = \frac{\sum_{i=v(15\mathrm{th})}^{v(85\mathrm{th})} \{c[g(i)]\cdot g(i) - M_{\mathrm{R}70\%}\}^2}{t\{c[g(i)]\}} \tag{2}$$

$$t\{c[g(i)]\} = \sum_{i=v(15\mathrm{th})}^{v(85\mathrm{th})} c[g(i)] \tag{3}$$

where $g(i)$ and $c[g(i)]$ are the gray level and frequency of the ith percentile, respectively; $v(15\mathrm{th})$ and $v(85\mathrm{th})$ are the gray levels at the 15th and 85th percentile, respectively; $t\{c[g(i)]\}$ is the total frequency of the range (15th, 85th); and $M_{\mathrm{R}70\%}$ and $V_{\mathrm{R}70\%}$ are the mean and variance of the R signal intensities, respectively, in the range (15th, 85th).

Step 2

The whole image was divided into subsets and the mean $[M(j, k)]$ and variance $[V(j, k)]$ of a *subset* (j, k) were computed. This can be described as follows:

$$M(j,k) = \frac{\sum_{\mathrm{counti}=1}^{n} \sum_{\mathrm{countj}=1}^{m} g(\mathrm{countj},\mathrm{counti})}{nm} \tag{4}$$

$$V(j,k) = \frac{\sum_{\mathrm{counti}=1}^{n} \sum_{\mathrm{countj}=1}^{m} [M(j,k) - g(\mathrm{countj},\mathrm{counti})]^2}{nm} \tag{5}$$

where $n = 48$ and $m = 64$.

Step 3

The statistics are then calculated according to:

$$S^2_{p(j,k)} = \frac{(t\{c[g(i)]\} - 1)V^2_{70\%} + (nm - 1)V(j,k)^2}{t\{c[g(i)]\} + nm - 2} \tag{6}$$

$$t_{\mathrm{obs}(j,k)} = \frac{M_{70\%} - M(j,k)}{S_{p(j,k)}\sqrt{1/t\{c[g(i)]\} + 1/(nm)}} \tag{7}$$

Step 4

If the absolute value of $t_{\mathrm{obs}(j,k)}$ is greater than a threshold, then assign *subset* (j, k) as a potential defect subset.

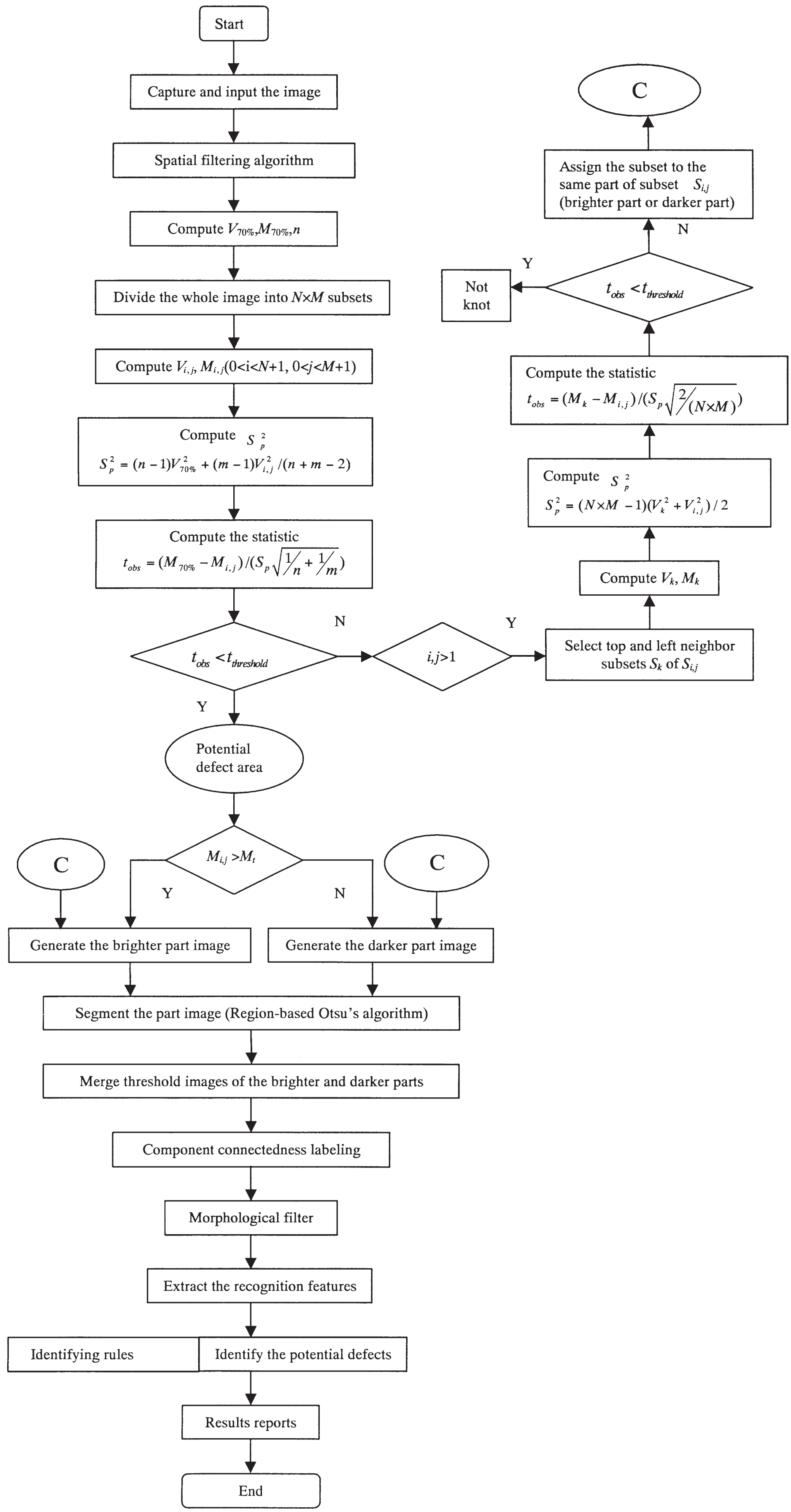
Step 5

Every subset should be tested by the above *t*-test operation. After the *t*-test operation, the potential defect image was segmented into a binary picture (Fig. 4) by the frame-based method of Otsu.[3,10] To form the complete potential defect areas from the discrete points after segmenting, the 4-adjacent connectedness component labeling operation was applied.[11]

Rule-based identification of a potential defect region

In this study, a rule-based approach[12] was adopted to identify the potential defect region. For each of the potential defect regions located by the above procedure, statistical and geometric features were computed from the image data. Currently, eight basic features have been derived to identify sound knots, dead knots, and clear wood. Additional

Fig. 2. The flowchart of the program



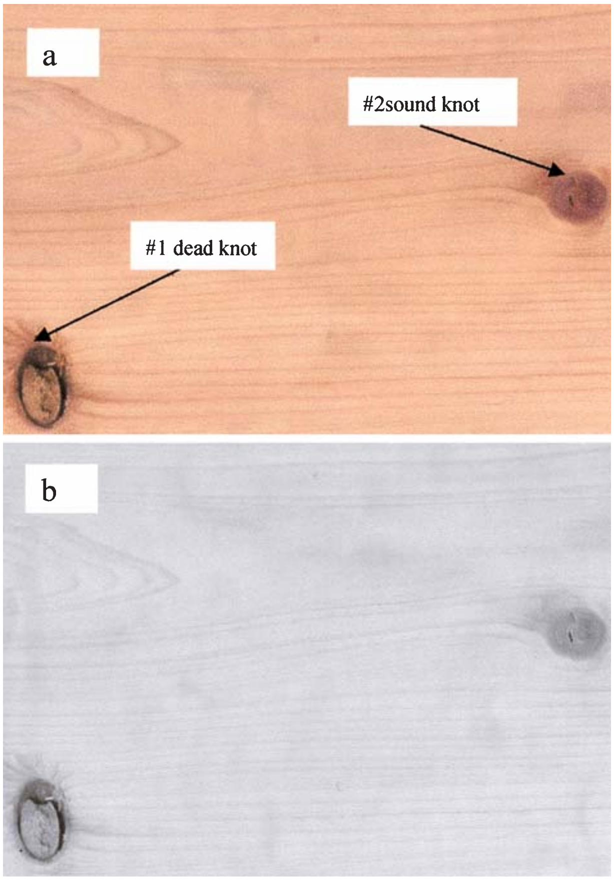


Fig. 3. The RGB color picture (**a**) and the R signal picture (**b**)

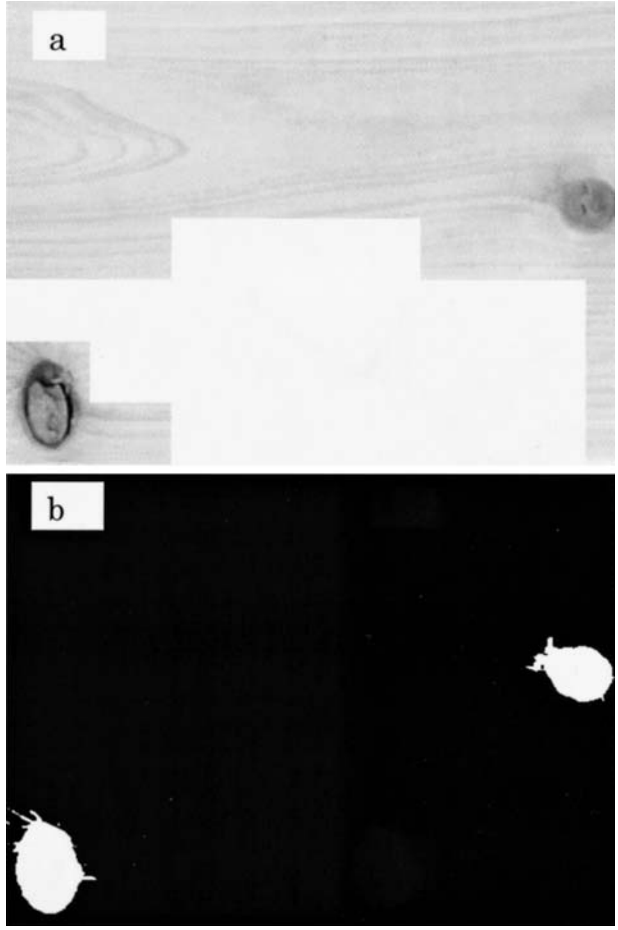


Fig. 4a,b. The R signal picture after pre-processing. **a** After *t*-text analysis. **b** After connectedness component labeling

features will be added to the system as other defects need to be recognized or as current defects need to be identified better. The following are brief descriptions of eight basic features that are computed from a potential defect region:

1. The means (M_R, M_G, M_B) and variances (V_R, V_G, V_B) of the R, G, and B signals are obtained for all pixels contained in a potential defect area. These features are described by the following formulas:

$$M_R = \frac{\sum_{i=1}^{i=N}\sum_{j=1}^{j=M} R(i,j)}{NM} \tag{8}$$

$$M_G = \frac{\sum_{i=1}^{i=N}\sum_{j=1}^{j=M} G(i,j)}{NM} \tag{9}$$

$$M_B = \frac{\sum_{i=1}^{i=N}\sum_{j=1}^{j=M} B(i,j)}{NM} \tag{10}$$

$$V_R = \sqrt{\frac{\sum_{i=1}^{i=N}\sum_{j=1}^{j=M} \left[M_R - R(i,j)\right]^2}{NM}} \tag{11}$$

$$V_G = \sqrt{\frac{\sum_{i=1}^{i=N}\sum_{j=1}^{j=M} \left[M_G - G(i,j)\right]^2}{NM}} \tag{12}$$

$$V_B = \sqrt{\frac{\sum_{i=1}^{i=N}\sum_{j=1}^{j=M} \left[M_B - B(i,j)\right]^2}{NM}} \tag{13}$$

2. The geometric features of compactness and roundness are obtained by computing the geometric feature. The method used to compute these features was described in our previous report.[3]

Based on these eight basic features, each potential defect area has a confidence vector to describe the belief that the area belongs to sound knots, dead knots, or clear wood. To properly determine the identifying rules, 222 samples, which consisted of 142 sound knot and 80 dead knot regions, were used as a set of training samples to generate rule thresholds. For every training sample, the eight basic feature values were computed and then the individual feature population distributions (feature histograms) were formed. Thresholds were visually determined from the individual feature histograms. All thresholds and identifying rules are

Table 1. The rules identifying clear-wood from potential defect wood

		Confidence value	
Features	Thresholds	PDW	CW
Compactness $\leq$ 1.23			
M_G	$M_G \in [97,151]$	0.5	0.5
	$M_G \notin [97,151]$	1.0	0
M_R	$M_R \in [118,218]$	0.5	0.5
	$M_R \notin [118,218]$	1.0	0
V_G	$V_G \in [6,17]$	0.5	0.5
	$V_G \notin [6,17]$	1.0	0
V_R	$V_R \in [5,16]$	0.5	0.5
	$V_R \notin [5,16]$	1.0	0
Compactness > 1.23			
M_G	$M_G \in [97,151]$	0	1.0
	$M_G \notin [97,151]$	0.5	0.5
M_R	$M_R \in [118,218]$	0	1.0
	$M_R \notin [118,218]$	0.5	0.5
V_G	$V_G \in [6,17]$	0	1.0
	$V_G \notin [6,17]$	0.5	0.5
V_R	$V_R \in [5,16]$	0	1.0
	$V_R \notin [5,16]$	0.5	0.5
Roundness $\in$ [0.4,2.5]			
M_G	$M_G \in [97,151]$	0.5	0.5
	$M_G \notin [97,151]$	1.0	0
M_R	$M_R \in [118,218]$	0.5	0.5
	$M_R \notin [118,218]$	1.0	0
V_G	$V_G \in [6,17]$	0.5	0.5
	$V_G \notin [6,17]$	1.0	0
V_R	$V_R \in [5,16]$	0.5	0.5
	$V_R \notin [5,16]$	1.0	0
Roundness $\notin$[0.4,2.5]			
M_G	$M_G \in [97,151]$	0	1.0
	$M_G \notin [97,151]$	0.5	0.5
M_R	$M_R \in [118,218]$	0	1.0
	$M_R \notin [118,218]$	0.5	0.5
V_G	$V_G \in [6,17]$	0	1.0
	$V_G \notin [6,17]$	0.5	0.5
V_R	$V_R \in [5,16]$	0	1.0
	$V_R \notin [5,16]$	0.5	0.5

PDW, Potential defect wood; CW, clear wood

Table 2. The rules identifying sound knots from dead knots

		Confidence value	
Features	Thresholds	SK	DK
M_B	$M_B \in [57,116]$	1.0	0
	$M_B \in [35,85]$	0	1.0
V_B	$V_B \in [10,33]$	1.0	0
	$V_B \in [25,51]$	0	1.0
V_G	$V_G \in [12,34]$	1.0	0
	$V_G \in [27,52]$	0	1.0
V_R	$V_R \in [18,37]$	1.0	0
	$V_R \in [32,54]$	0	1.0

SK, Sound knot; DK, dead knot

shown in Tables 1 and 2. As shown in Table 1, the geometric features of compactness and roundness are set as the top layers in the two-layer rules for the separation of clear wood from defects. Based on the geometric features, 16 subrules were built. To separate knots into sound knots and dead knots, another four subrules were built as shown in Table 2. For each potential defect area, such rules assign individual values to its confidence value. As an example, rules using feature M_B are expressed as follows:

If roundness $\in$ [0.4, 2.5] then
  If $M_B \in$ [97,151] then
    $\mathrm{Cv}[M_B(i),\mathrm{clearwood}] = \mathrm{Cv}[M_B(i),\mathrm{clearwood}] + 0.5$
    $\mathrm{Cv}[M_B(i),\mathrm{defectwood}] = \mathrm{Cv}[M_B(i),\mathrm{defectwood}] + 0.5$
  Else
    $\mathrm{Cv}[M_B(i),\mathrm{clearwood}] = \mathrm{Cv}[M_B(i),\mathrm{clearwood}] + 1.0$
    $\mathrm{Cv}[M_B(i),\mathrm{defectwood}] = \mathrm{Cv}[M_B(i),\mathrm{defectwood}]$
  Endif
Else
  If $M_B \in$ [97, 151] then
    $\mathrm{Cv}[M_B(i),\mathrm{clearwood}] = \mathrm{Cv}[M_B(i),\mathrm{clearwood}] + 1$
    $\mathrm{Cv}[M_B(i),\mathrm{defectwood}] = \mathrm{Cv}[M_B(i),\mathrm{defectwood}]$
  Else
    $\mathrm{Cv}[M_B(i),\mathrm{clearwood}] = \mathrm{Cv}[M_B(i),\mathit{clearwood}] + 0.5$
    $\mathrm{Cv}[M_B(i),\mathrm{defectwood}] = \mathrm{Cv}[M_B(i),\mathrm{defectwood}] + 0.5$
  Endif
Endif

The applying rule is in fact a voting process where a higher vote is given to the strong evidence and a lower vote to the weaker evidence. The total vote of the potential defect area in rules to distinguish clear wood from defect wood can be expressed by the following formulas:

$$\mathrm{TV_l}(\mathrm{clearwood}) = \sum_{\mathrm{countk}=1}^{T_r} \mathrm{Cv}\left[F(\mathrm{countk}),\mathrm{clearwood}\right] \tag{16}$$

$$\mathrm{TV_l}(\mathrm{defectwood}) = \sum_{\mathrm{countk}=1}^{T_r} \mathrm{Cv}\left[F(\mathrm{countk}),\mathrm{defectwood}\right] \tag{17}$$

where F(countk) is the *countk*th feature, Cv(F(countk), clearwood) and Cv(F(countk),defectwood) are the evaluating votes of the *countk*th feature for clear wood and defect wood, respectively, $\mathrm{TV_l}$(clearwood) and $\mathrm{TV_l}$(defectwood) are the total values for the classification of clear wood and defect wood, respectively, and T_r is the total number of the feature. In this report, T_r is 4(M_B, M_R, V_G, V_R).

After the potential defect regions were defined, they were passed to the identifying rules for separating knots into sound knots and dead knots. As an example, rules using feature M_G are shown as follows:

  $\mathrm{Cv}[M_G(i),\mathrm{soundknot}] = 0$
  $\mathrm{Cv}[M_G(i),\mathrm{looseknot}] = 0$
  If $\mathrm{TV_l}$(defectwoood) >= $\mathrm{TV_l}$(clearwood) then
    If $M_G \in$ [57,116] then
    $\mathrm{Cv}[M_G(i),\mathrm{soundknot}] = \mathit{Cv}[M_G(i),\mathrm{soundknot}] + 1$
    $\mathrm{Cv}[M_G(i),\mathrm{looseknot}] = \mathit{Cv}[M_G(i),\mathrm{looseknot}]$
  Elseif $M_G \in$ [35,75] then
    $\mathrm{Cv}[M_G(i),\mathrm{soundknot}] = \mathrm{Cv}[M_G(i),\mathrm{soundknot}]$
    $\mathrm{Cv}[M_G(i),\mathrm{looseknot}] = \mathrm{Cv}[M_G(i),\mathrm{looseknot}] + 1$
  Endif
Endif

Another three subrules are also applied to vote the defect area and the total vote can be expressed by the following formulas:

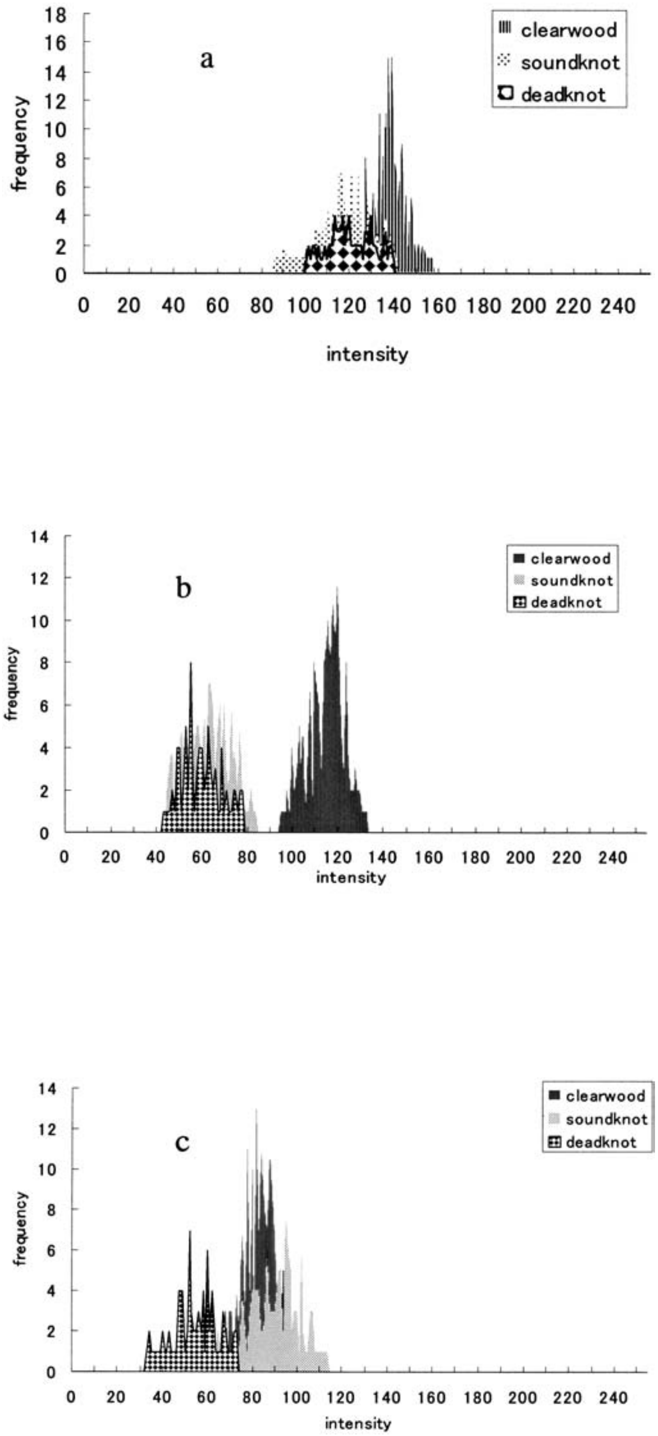


Fig. 5a–c. The feature histograms of means for R, G, B signals. **a** R signal, **b** G signal, **c** B signal

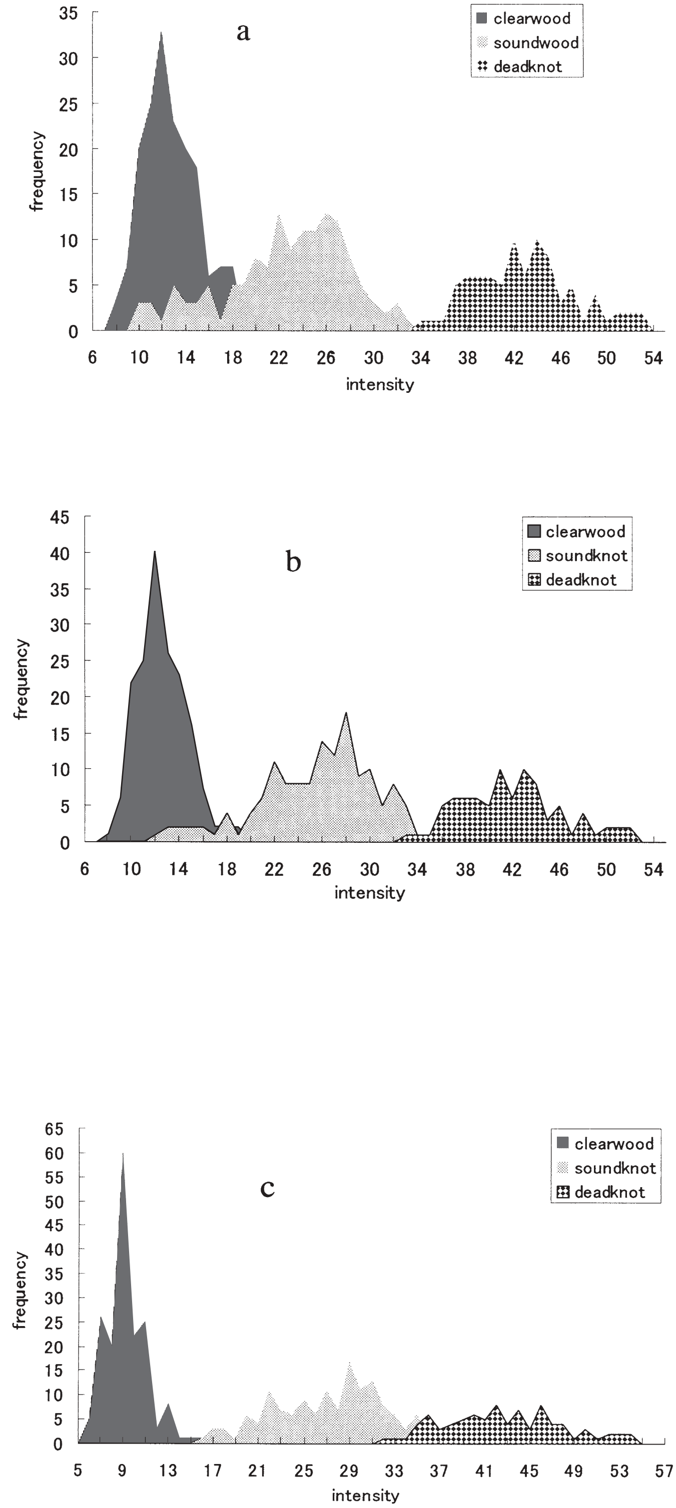


Fig. 6a–c. The feature histograms of variances for R, G, B, signals. **a** R signal, **b** G signal, **c** B signal

$$\mathrm{TV_1(soundknot)} = \sum_{\mathrm{countl}=1}^{T_r'} \mathrm{Cv}\left[F(\mathrm{countl})\right] \tag{18}$$

$$\mathrm{TV_1(looseknot)} = \sum_{\mathrm{countl}=1}^{T_r'} \mathrm{Cv}\left[F(\mathrm{countl})\right] \tag{19}$$

where F(countl) is the *countl*th feature, T_r' is the total number of the feature, and $\mathrm{TV_1}$(soundknot) and $\mathrm{TV_1}$(looseknot) are the total votes for the classification of the sound knot and the dead knot, respectively. In this report, T_r' is 4 (M_G, V_R, V_G, V_B).

Table 3. The values of recognition features and identifying results

NOPDR	Values of recognition features								Identifying votes				
	Roundness	Compactness	M_B	M_G	M_R	V_B	V_G	V_R	CW	PDW	SK	DK	Classification
#1	0.79	1.01	56.5	82.4	118.8	25.1	30.6	39.9	1.0	7.0	3.0	4.0	DK
#2	1.34	1.02	68.4	86.5	136.7	10.2	15.4	19.1	2.0	6.0	4.0	0	SK

NOPDR, Number of potential defect regions

Table 4. The accuracy of the system

Classification	Total samples	Samples located correctly	Locating accuracy	Samples identified accurately	Identifying accuracy	Final detecting accuracy
Sound knot	54	50	92.6%	46	92.0%	85.2%
Dead knot	35	34	97.1%	32	94.1%	91.4%
					Total detecting accuracy	87.6%

Results and discussion

The defects of sound and dead knots are associated with surface color. This characteristic can be used to detect knots by using a CCD-camera. As shown in Fig. 3, two knots (one sound knot and one dead knot) are manifested well in the sample image. The monochrome camera was used to perform the defect detection of the wood surface.[13] Previous studies indicated that two components of a color space were required to detect the defect in Douglas fir.[14] In the present study, the single channel signal image (R signal) was used to locate the potential defect regions, and the R, G, and B signals were all used for identification because the R, G, and B signals were all testified to be useful information to enhance the identification of sound and dead knots.

To reduce processing time and storage space and to enhance the separation of potential wood defects, the *t*-test analysis was performed on the image. Eighty percent or more of the total area within a board is clear wood. Therefore, it is critical that potential defects are detected at an early stage of processing if processing time is to be minimized. Once this has been achieved, more time can be applied to those regions believed to contain a defect that usually occupy a very small percentage of the whole image. As shown in Fig. 4, most of the clear wood was eliminated. Meanwhile the potential defect wood was left after the *t*-test analysis. To more accurately locate the potential defect regions, the automatic image-based selection threshold of Otsu's algorithm was performed. As shown in Fig. 4, the R signal picture is separated into a binary picture that correctly expresses the potential defect and clear wood areas. In this study, one sound knot and one dead knot of the training sample were correctly located by the image-processing course proposed.

To identify the sound and dead knots, the identifying rules were based on eight basic statistical and geometrical features. A series of samples containing sound knots and/or dead knots was used to provide training data to form the feature histograms. Thresholds that separated the population distributions of features into discrete groups and created the identifying rules were visually determined from the feature histograms. As shown in Figs. 5 and 6, the features of M_G, M_R, V_G, and V_R are valuable to distinguish clear wood from the defect wood and M_B, V_B, V_G, and V_R provide the dominant differences to help distinguish the sound knot from the dead knot. Considering the manifestation of all eight basic features, the identifying rules were created as shown in Tables 1 and 2. As shown in Table 1, the two-layer rules that distinguish clear wood from defect wood were based on the two geometrical features of compactness and roundness, and the four statistical features M_G, M_R, V_G, and V_R. As shown in Table 2, the rules that distinguish sound knots from dead knots were based on the four statistical features M_B, V_B, V_G, and V_R. One sound knot and one dead knot of the training sample were used to explain the processing procedure of the system and to test the efficiency of the identifying rules. The feature values and the identification results are shown in Table 3. The results indicate that all the defects were identified correctly.

Another series of samples containing single or multiple sound and/or dead knots was selected at random to thoroughly test the efficiency and accuracy of the system. There were 54 sound knots and 35 dead knots on the surfaces of these samples. As shown in Table 4, the locating accuracies for sound knots and dead knots were 92.6% and 97.1%, respectively. The identifying accuracies for sound knots and dead knots were 92.0% and 94.1%, respectively. The final detection accuracies for sound knots and dead knots were 86.6% and 91.4%, respectively, and the overall detection accuracy was 87.6%.

Conclusions

The results of this study showed that the rule-based vision system is effective for detecting the defects of sound knots and dead knots that are well manifested in the RGB image. The image-processing course that located the potential defect regions of sound knots and dead knots on sugi was developed and tested. The accuracies of locating sound knots and dead knots were 92.6% and 97.1%, respectively. The rule-based approach was used to identify sound knots and dead knots and the identifying accuracies of sound knots and dead knots were 92.0% and 94.1%, respectively. The overall detection accuracy of the system was 87.6%.

Rule-based technology is efficient in defect classification. However, additional features will require consideration as other defects need to be recognized or as current defects need to be more clearly identified.

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